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SPATIAL-TEMPORAL CARBON SEQUESTRATION UNDER LAND USE AND LAND COVER CHANGE

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Abstract

In this research carbon (C) sequestration of the Blue Ridge ecoregion of North America was investigated using the General Ensemble biogeochemical Modeling System (GEMS). GEMS assimilated historical land use and land cover change (LUCC) data within ten 20-km by 20-km sampling blocks in the ecoregion and performed biogeochemical C simulations for the period of 1973 – 2000. The LUCC data were derived from both low spatial resolution census and survey data (forest structure and agricultural cropping practices), and from high spatial resolution sequential land cover maps. The land cover maps were derived from Landsat remote sensing data at 60-meter resolution. GEMS used Monte Carlo approaches to deal with some spatial and temporal LUCC scaling issues such as initialization of forest age and crop species. It also prescribed the land use activities such as forest selective cuttings that were not reflected in the land cover change maps. Results showed that this ecoregion was a C sink during the simulation period. The sink averaged 100 – 120 g C m^{-2} yr^{-1} with a major portion (50-80%) attributed to living biomass and smaller portions attributed to soil and harvested C. Net primary productivity (NPP) in Blue Ridge ecoregion was about 600 to 800 g C m^{-2} yr^{-1}. Based on the 10 sample blocks, estimation error of C sequestration at 95% confidence level is about 15 to 45 g C m^{-2} yr^{-1}, varying by year. Model simulations also indicated that LUCC played a significant role in determining the magnitude of carbon sink strength in the region. Without considering the dynamics of LUCC, the C sink strength would be underestimated by 30 to50 percent.

INTRODUCTION

The U.S. terrestrial ecosystems might significantly contribute to the global carbon (C) sink, but large uncertainty still remains regarding its spatial and temporal patterns, and driving forces (Houghton et al., 1999; Ciais et al., 2000; Pacala et al., 2001; Hurtt et al., 2002; Liu et al., 2004). Large-scale ecosystem C dynamics is complicated, not only because of the influences of natural processes such as climate change and variability, but also the impacts of human activities. Land use and land cover change (LUCC) is one of the major factors that affect the carbon dioxide (CO_2) exchange between terrestrial ecosystems and the atmosphere. Due to difficulties in mapping LUCC dynamics over large areas, consistent LUCC data are rarely available at the regional to global scales. This might be one of the reasons that few regional to global scale C models are capable of assimilating dynamic, detailed LUCC data. It is only recently that researchers started to deal with LUCC data for large regions using an integrated simulation approach. For example, the General Ensemble-based biogeochemical Modeling System (GEMS) focuses on LUCC data assimilation in biogeochemical modelling by assimilating low spatial resolution inventory and census data, as well as high spatial resolution data derived from remote sensing (Liu et al., 2004).

As part of an effort to quantify the contemporary carbon sources and sinks and their spatial distribution in the United States, this study used GEMS to estimate the C dynamics of the Blue Ridge ecoregion. Our specific objectives are to estimate the magnitude and temporal change of carbon sources and sinks at the ecoregion scale with measures of uncertainty, and determine the contribution of LUCC to the dynamics of carbon.

SITES AND METHODS

The Blue Ridge ecoregion

The Blue Ridge ecoregion is located in the southern Appalachia mountain area in the Southeastern part of the United States. It covers parts of Virginia, North Carolina, Tennessee, and Georgia and has a total area of about 44,500 square kilometers. It has one of the most diverse assemblages of plants and animals found in the world's temperate deciduous forests. More than 80% of the area is forest and almost all of the forest is re-growth following cutting. These forests are being managed for timber extraction, but changes in public demand and Forest Service policy may eventually balance consumptive use with an increase in non-consumptive uses (Stephenson et al., 1993).

Overview of the modelling system GEMS

The spatial simulation unit in GEMS is the joint frequency distribution (JFD) case, which is obtained from the overlay operations of land cover maps, soil type, atmospheric N deposition, and climate coverages (Figure 1). A JFD case contains one or multiple, homogeneous, connected or isolated land pixels, representing a unique combination of the values from the environmental GIS layers used in the overlay operation.

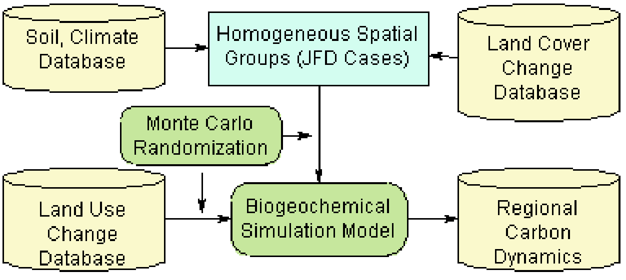

Figure 1: Conceptual GEMS framework.

Once a JFD table is generated, the spatial location and extent of each JFD case in the table is fixed, whether the JFD case is formed by a number of polygons or only by one polygon, or even only one land pixel. However, in temporal dimension a JFD case may change its land cover type for successive time periods. On the spatial dimension, all the JFD cases of a region together (i.e., the JFD table) present land cover change features (such as the area weights of land cover types) in space and time.

The underlying ecosystem level biogeochemical model that GEMS currently uses is the Erosion-Deposition-Carbon-Model (EDCM) of Liu et al. (2003). For each JFD case GEMS prepares a set of input files and parameters that are specific to the JFD case and suitable for EDCM simulation. These input files and parameters include land cover type, climate conditions, soil property, forest age, crop type, and some land use specifications such as crop rotation, fertilization, forest selective cutting, crop harvesting, etc. Some of these initialization processes are done by a Monte-Carlo randomization. For example, a forest JFD case was assigned an initial forest age based on the forest age class structure at the state level derived from the Forest Service's Forest Inventory and Analysis (FIA) database; an agricultural JFD case was assigned an initial crop species according to the crop composition derived from agricultural census data. Multiple EDCM model runs were performed for each JFD case to incorporate the uncertainty of input data. Model simulated results for the JFD cases were then aggregated to sampling block and ecoregion levels.

Land use and land cover change, and its representation in modelling

For the Blue Ridge ecoregion, ten 20-km by 20-km sampling blocks were randomly selected for land cover change detection for the U.S. Land Cover Trends Project (Loveland et al., 2002). The land cover types were derived from five dates of the Landsat MSS, TM, and ETM+ data (nominally 1973, 1980, 1986, 1992, and 2000), which were analyzed at 60-meter resolution.

The following procedures were implemented in GEMS to assimilate the LUCC data:

1. Land cover conversion, as indicated by different land cover classes at two consecutive points in time, was assumed to occur during the interval defined by the two points. The specific year for the conversion was estimated randomly.
2. Even if no land cover change was detected between two consecutive remote sensing observations, additional land use activities (e.g., clearcutting and selective cutting) might be prescribed to account for the activities that might have missed by the remote sensing. For example, because of the fast recovery of spectral reflectance after reforestation in the region, an interval of 8 years might be too long for detecting clearcutting activities that occurred during the early part of the time interval. How far back the remote sensing technique can go to detect clearcutting activities depends on the growth rates of forests. With fast growth, a clear cut could be missed in the time interval for the remotely sensed data. In this region, our experience suggested an effective time frame of 5 years. If the time period between two consecutive remote sensing observations is longer than the effective time frame, additional clearcutting events were scheduled by assuming the annual clearcutting rate detected by remote sensing can be applied to the entire time period. These additional clearcutting events were not randomly assigned to the randomly selected JFD cases because some JFD cases occupy large areas in space and cutting forests over a large area at any given time is not likely to have actually happened. To avoid cutting a big area, we applied an additional cutting probability to all the forest JFD cases. Doing so, a forest JFD case was subdivided into several temporary JFD sub-cases, with one representing no cutting and others representing additional cutting within the time interval between two remote sensing observations. In this study, selective cutting probability (which was not observed by remote sensing) was derived from the FIA database and used to schedule selective cutting events on forest lands.
3. A Monte Carlo approach was used to initialize the model. For example, forest age was assigned according to state-wide forest age distribution derived from FIA data. Once forest age was assigned, the corresponding initial standing biomass was estimated from the age-biomass relationship derived from FIA. The general land cover class "agricultural land" used in LUCC characterization was downscaled to crop species according to the crop composition information from agricultural

census. Crop rotation probabilities were applied to simulate the inter-annual crop transitions.

Estimation of carbon sources and sinks

The EDCM embedded in GEMS was modified from the CENTURY model (Liu et al., 2003). CENTURY has well-tested modules for simulating carbon dynamics at the ecosystem level and has been applied to various ecosystems including crops, pastures, forests and savannas (Parton et al., 1987; Parton et al., 1994; Schimel et al., 1991). In this study most model parameters are set to their default values. Details about the development of the EDCM model can be found in Liu et al. (2003, 2004). In this study, GEMS was further adapted to use a new historical climate dataset CRU TS 2.0 (Mitchell et al., 2003), and the potential NPP estimates derived from the Moderate Resolution Imaging Spectro-radiometer (MODIS) product (Heinsch et al., 2003; see http://www.ntsg.umt.edu/modis/ MOD17UsersGuide.pdf).

Twenty model simulations were performed for each JFD case to incorporate the variability and uncertainty of input data into the modeling processes. Our simulations indicated that 20 model runs usually gave stable estimates of carbon dynamics at the block scale. Model simulated results were analyzed using SAS programs. Major simulation outputs include soil organic C (SOC) stock, biomass C stock, NPP, and forest removal.

Carbon sources and sinks were calculated as a summation of net annual changes of SOC, biomass C, and C removed by forest harvesting. The harvested wood C (HWC) pool was initialized using the assumption that the HWC pool size in the 1970s was 80% of the pool size during 1990s, according to the temporal change of HWC stock at the national scale (Skog and Nicholson, 1998). More information was given on the treatment of HWC in Liu et al. (2004). Grain removed each year was assumed to have a short turnover time and respires quickly, so annual net biomass C change of agricultural product was taken as zero. For each sample block, the C sequestration strength was aggregated from the mean C output of each JFD case using a SAS program. Based on the ten sample blocks, the ecoregion’s average C sequestration strength and its standard error were calculated.

Data sources

The high resolution LUCC information was developed using remote sensing for the US Land Cover Trends project, providing the most accurate land cover change information ever obtained in the U.S. (Loveland et al., 2002). Soil coverage was from the U.S. State Soil Geographic (STATSGO) database (USDA, 1994). Climatic coverages were converted from the CRU TS 2.0 dataset (Mitchell et al., 2003). The total atmospheric nitrogen deposition from wet and dry sources was from the National Atmospheric Deposition Program (http://nadp.sws.uiuc.edu/). Other land use data were from sources including the FIA database and the National Resources Inventory (NRI) database developed by the Natural Resources Conservation Service, U.S. Department of Agriculture (http://www.nrcs.usda.gov/tevhnical/NRI). MODIS data were downloaded from the University of Montana (http://www.ntsg.umt.edu/MODISCon/html/npp.html).

RESULTS

Land cover change in Blue Ridge ecoregion from 1973 to 2000

Although the Blue Ridge ecoregion has been altered by agriculture, logging, and most recently, suburban sprawl, human disturbances were relatively less intensive than its surrounding ecoregions, probably due to its elevation and conservation policies. In general, based on the ten 20-km by 20-km sampling blocks, the Blue Ridge ecoregion's overall net land cover change from 1973 to 2000 was around 2.37%, most of which was a decrease of forest area (from 83.1% to 81.8%) and the expansion of urban and developed land (from 6.0% to 7.2%). Agricultural land and grass and shrub land remained unchanged at 10.3% and 0.1%, respectively.

Simulated model outputs of sample blocks

The GEMS was calibrated with MODIS NPP data and FIA biomass data. Simulated NPP values and the MODIS NPP estimates on each of the ten sample blocks were shown on Figure 2. The MODIS NPP values are the averages of all the land pixels in a sample block. GEMS average NPP of the ten sample blocks was 705 g C m^{-2} yr^{-1} while the MODIS average NPP for the ten sample block was 695 g C m^{-2} yr^{-1}.

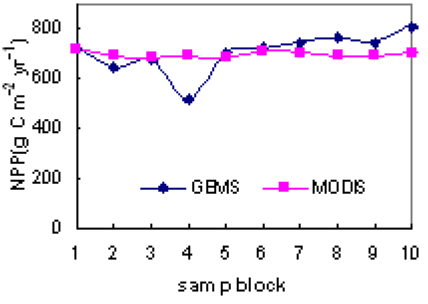

Figure 2: NPP comparison between MODIS and GEMS outputs.

There are also general matches between simulated forest biomass estimates and the FIA data where state level (Virginia, North Carolina, Tennessee, and Georgia) average forest biomass data are available for several inventory time (Figure 3).

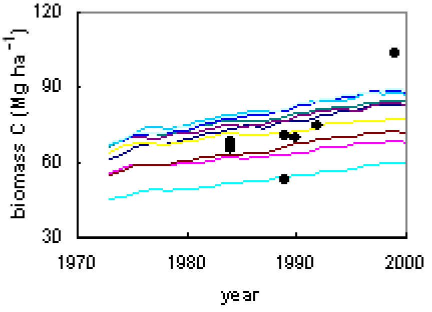

Figure 3: Biomass comparison between GEMS output and FIA data. Lines are the simulated biomass C changes within the 10 sampling blocks.

Selected outputs for the ten sample blocks are shown in Figure 4. Soil C in most blocks increased during the simulation period. Biomass increased in all the sample blocks, with a strong positive relationship with NPP. Simulated NPP varied between 4 and 8 Mg C ha^{-1} yr^{-1}. Average forest biomass C removal increased slightly (from 0.5 to 0.8 Mg C ha^{-1} yr^{-1}) during the simulation period.

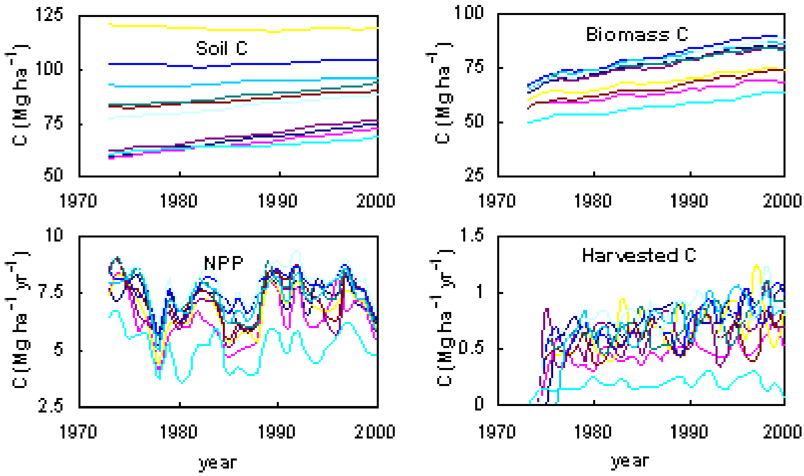

Figure 4: Simulated carbon outputs (soil, biomass, NPP and harvest) of ten sample blocks.

Regional C source and sink

The regional C sequestration strength was estimated based on the ten sample blocks. Net C change (i.e., C source or sink) was the summation of net C changes in biomass, soil and harvested wood (Figure 5a). No strong relationship was found between the inter-annual variability of C change and the changes of harvesting C and soil C. The inter-annual variability of C sinks and sources in the region was closely related to the inter-annual variability of biomass C. Because the C removal through timber harvesting was relatively stable during the simulation period, we believe that the biomass fluctuation was mainly caused by the variations of annual NPP values, which in turn were mainly determined by inter-annual climate variations. Based on the ten sample blocks, net annual C change in the ecoregion varied from –0.5 to 2.5 Mg C ha^{-1} yr^{-1} (Figure 5b), indicating that this ecoregion can be a C sink (positive) or a C source (negative) depending on the fluctuations of climate and land use activities.

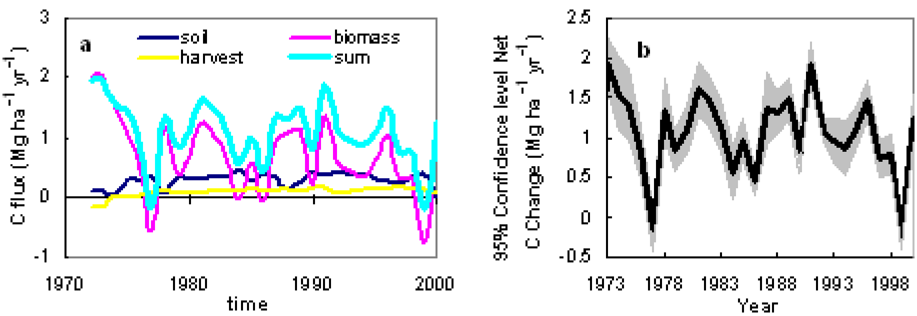

Figure 5: (a) Inter-annual variations of C gain, (b) estimation errors on net C gain.

The net C gain in Blue Ridge can be attributed to three pools: biomass, soil, and wood product (Figure 6). Most of the sequestered C went into the biomass pool during the simulation period. But the C sink attributed to biomass has been decreasing and those attributed to soil and wood products have been increasing over time. This may indicate that the forests at the beginning of the simulation were younger than those at the end of the simulation, and harvested C was increasing (Figure 4).

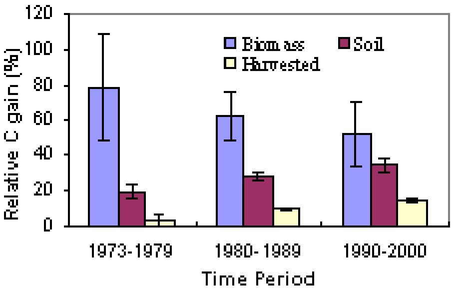

Figure 6: Relative allocation of net C gains to biomass, soil and wood product.

LUCC impact on C budget

We estimated the impacts of land cover change on C source and sink by comparing simulations with static and dynamic land cover. Figure 7 shows the comparison of net C gains based on the time series of five land cover maps (dynamic land cover) and net C gains based on only one land cover map (static land cover with no forest clearcutting). It can be seen that simulation using static 1973 land cover had a much higher C gain (30 to 50%) than the simulation using 5 dates of dynamic land cover. The difference was about 0.7 to 1.0 Mg C ha^{-1} yr^{-1}, higher than the amount of hardwood C removal. The results suggested that dynamic LUCC information is critical for the quantification of C sources and sinks at the regional scale.

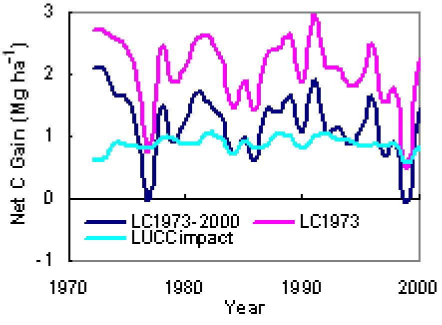

Figure 7: Static and dynamic land cover impact on ecoregion C sequestration.

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REFERENCES

Ciais, P., Peylin, P. and Bousquet, P., 2000: Regional biospheric carbon fluxes as inferred from atmospheric CO_2 measurements. *Ecological Applications* 10, 1574-1589.

Heinsch, F.A., Reeves, M., Votava, P., Kang, S., Milesi, C., Zhao, M., Glassy, J., Jolly, W.M., Loehman, R., Bowker, C.F., Kimball, J.S., Nemani, R.R. and Running, S.W., 2003: *User's Guide GPP and NPP (MODIS17A2/A3) Products NASA MODIS L and Algorithm*. http://www.ntsg.umt.edu/modis/MOD17UsersGuide.pdf.

Houghton, R.A., Hackler, J.L. and Lawrence, K.T., 1999: The U.S. carbon budget: Contributions from land-use change. *Science* 285, 574-578.

Hurtt, G.C, Pacala, S.W., Moorcroft, P.R., Caspersen, J., Shevliakova, E., Houghton, R.A. and Moore, B. III, 2002: Projecting the future of the U.S. carbon sink. *Proc. Natl. Acad. Sci. USA* 99(3), 1389-1394.

Liu, S., Bliss, N., Sundquist, E. and Huntington, T.G., 2003: Modeling carbon dynamics in vegetation and soil under the impact of soil erosion and deposition. *Global Biogeochemical Cycles* 17(2), 1074, DOI: 10.1029/2002GB002010.

Liu, S., Loveland, T.R. and Kurtz R.M., 2004: Contemporary carbon dynamics in terrestrial ecosystems in the Southeastern Plains of the United States. *Environmental Management*, DOI: 10.1007/s00267-003-9152-z

Loveland, T.R., Sohl, T.L., Stehman, S.V., Gallant, A.L., Sayler, K.L. and Napton, D.E., 2002: A strategy for estimating the rates of recent United States land-cover Changes. *Photogrammetric Engineering & Remote Sensing* 68(10), 1091-1099.

Mitchell, T.D., Carter, T.R., Jones, P.D., Hulme,M., New, M., 2003: A comprehensive set of high-resolution grids of monthly climate for Europe and the globe: the observed record (1901-2000) and 16 scenarios (2001-2100). Journal of Climate: submitted.

Pacala, S.W., Houghton, R.A., Birdsey, R.A., Heath, L., Sundquist, E.T., Stallard, R.F., Ciais, P., Moorcroft, P., Caspersen, J.P., Shevliakova, E., Moore, B., Kohlmaier, G., Holland, E., Gloor, H., Harmon, M.E., Fan, S.M., Sarmiento, J.L., Goodale, C.L., Schimel, D., Field, C.B., Hurtt, G.C., Baker, D. and Peylin, P., 2001: Consistent land- and atmosphere-based U.S. carbon sink estimates. *Science* 292, 2316-2320.

Parton, W.J., Ojima, D.S. and Schimel, D.S., 1994: Environmental change in grasslands: assessment using models. *Climatic Change* 28, 111-141.

Parton, W.J., Schimel, D.S., Cole, C.V. and Ojima, D.S., 1987: Analysis of factors controlling soil organic matter levels in Great Plains grasslands. *Soil Science Society of America Journal*, 1173-1179.

Schimel, D.S., Brasswell, B.H., Holland, E., McKeown, R., Ojima, D.S., Painter, T.H., Parton, W.J. and Townsend, A.R, 1994: Climatic, edaphic, and biotic controls over storage and turnover of carbon in soils. *Global Biogeochemical Cycles* 8, 279-293.

Schimel, D.S., Kittel, T.G.F. and Parton, W.J., 1991: Terrestrial biogeochemical cycles: global interactions with the atmosphere and hydrology: *Tellus*, *Series A-B*, 43 A-B, 188-203.

Skog, K.E. and Nicholson. G.A., 1998: Carbon cycling through wood products: the role of wood and paper products in carbon sequestration. *Forest Products Journal* 48, 75-83.

Stephenson, S.L., Ash, A.N. and Stauffer. D.F., 1993: Appalachian oak forests. In: Martin, W.H. Boyce, S.G. and Echternacht, A.C. (Eds.). *Biodiversity of the Southeastern United States: Upland Terrestrial Communities*., John Wiley & Sons, New York, pp 255-303.

USDA, 1994: *State Soil Geographic (STATSGO) Data Base: Data use information*. Miscellaneous Publication Number 1492, 110 p. U.S. Department of Agriculture, Natural Resources Conservation Service, National Soil Survey Center, Lincoln, Neb.